Abnormality Management in Industrial Automation Systems

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***Abstract*—In this paper, a new concept for fault prevention in present and future industrial automation systems is presented. The aim of fault prevention is the identification of fault development processes while a system is still faultless. These processes can be difficult because they are only based on the past and the current system behaviour and the effects may not be visible yet. In order to countervail these problems, an abnormality management approach was developed to identify abnormalities in fault development processes. By means of this information, the same or systems of the same structure can be checked for these abnormalities in the future. Hence, the occurrence of faults can be prevented, the system availability can be increased and the costs can be reduced. Nowadays, the availability of systems are increasingly essential because a high productivity is needed for companies to remain competitive.**

***Index Terms*—abnormality management, fault prevention, abnormality identification, abnormality inspection**

I. Introduction

Globalization has been increasing in the last decades. For companies it has become more and more important to work as efficiently and effectively as possible. At the same time, the complexity and networking of industrial automation systems have been steadily increasing [1]. Therefore, there are a couple of new challenges in the fault management, fault detection and diagnosis sector. Faults can lead to system breakdowns and thereby to a lower production rate. Just as well, fault correction is more demanding due to the described increased complexity in the systems. One possibility to support the handling of these challenges is the prevention of system faults. Hereby, the idea is to identify abnormalities in the system behaviour, before a fault occurs. That is why, an innovative concept and a prototype for an abnormality management that automates the identification and the inspection of abnormalities have been developed at the Institute of Industrial Automation and Software Engineering at the University of Stuttgart. By means of this concept, operators can be supported and fault development processes can be identified automatically or rather diagnosed before a system gets out of order. A further positive effect is that also the maintenance costs can be reduced.

II. Basics for Fault Prevention in Industrial Automation Systems

In order to develop a concept for fault prevention in industrial automation systems it is important to understand the way faults develop. A fault development process can be noticed by abnormal system behaviour or rather by an abnormality in the system behaviour. Therefore, it is crucial to distinguish between an abnormality and a fault.

In general, an abnormality can be seen as a state, in which the system behaviour deviates from the normal condition [2]. Thereby, it is easy to recognize that the thresholds of abnormalities are quite fuzzy. In contrast, for faults there are several precise definitions, such as that a fault is a condition, which can cause a part or a complete system to fail [3]. Moreover, a fault produces an obvious loss of service [4]. Thus, in this context, an abnormality is a state, in which the system still works according to its defined specification, but it is recognizable that its permitted operation limits are exceeded.

A. *State of the Art in Fault Prevention*

Currently, there exist many fault prevention concepts, such as preventive or condition-oriented maintenance. An example is the concept of condition monitoring [5]. Condition monitoring is based on regular recording and analysis of the system behaviour, in order to identify fault development processes. For the data analysis, there are a couple of different methods, such as data mining or statistical algorithms [6].

However, due to the high complexity of industrial automation systems, data sets keep getting bigger. Consequently, big difficulties appear, because the large amount of data causes new challenges, such as the extraction of essential information [7]. Just as well, it is difficult to provide a reliable identification of abnormalities, because the knowledge about abnormalities must be generated during the development phase of the system and can vary from the actual behaviour. Out of these reasons, an innovative concept for an abnormality management has been developed at the Institute of Industrial Automation and Software Engineering (IAS).

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III. Concept for a Fault Prevention by Means of Abnormality Management

For the developed abnormality management for industrial automation systems (AMIAS), the mentioned problems and properties of current and future industrial automation systems were regarded properly. On one hand, it was aimed to reduce the amount of prevention relevant data and so the use of less complex analysis methods should be enabled. On the other hand, the concept should be applicable to a bunch of systems of the same structure. This decision was made due to the trend of connecting more and more systems and future projects, described frequently as the "Internet of Things" or "Industry 4.0" [8].

The term Industry 4.0 was first used at the Hannover Fair with the presentation of the "Industry 4.0" initiative. After the first industrial revolution of "Mechanization" resulting from the invention of the steam engine, the second of "Mass Production" with the help of electricity, and the third of "Digitalization" with the use of electronics and IT, this is the fourth industrial revolution, which will be expressed through the use of cyber-physical systems (CPS) and the Internet of Things and Services. Germany has a leading role in the field of CPS and can draw on almost 20 years of experience. Integrating cyber technologies makes products not only internet-enabled, but it also enables innovative services, for example, cost-effective and efficient internet web-based diagnostics, maintenance, and operation. This leads to the possibility of implementing new business models, operating concepts, and intelligent controls that consider the user and his or her individual needs. The goal of Industry 4.0 is the emergence of digital factories to be characterized by the following features, like intelligent networking, mobility, flexibility, integration of customers and new innovative business models.

In general, AMIAS consists of the two independent processes: A fault-based abnormality identification and a preventive abnormality inspection. Fault-based means that in AMIAS the abnormality identification takes place as recently as a fault occurred and a diagnosis of the fault was performed. In turn, the abnormality inspection is a continuous process, which is based on the result of the abnormality identification. Before the two processes are explained in details, the necessary precautions for the processes are presented in the following. The two processes require different knowledge or rather information, in order to make statements about abnormalities. Therefore, the following knowledge types were identified and defined: Fault knowledge, target process knowledge, and an inspection knowledge. In order to describe the concept feasibly, the important aspects are explained by means of a pressure loss in a water pipe in a fluid process automation system as an exemplary fault development cause. The fault knowledge is generated during the fault diagnosis process and contains fault-specific information, such as cause of faults, fault locations, and fault correction methods. With respect to the pressure loss, a possible cause could be a leak in the water pipe. The fault location could be the accurate position of the leak and a possible fault correction method could be the sealing of the leak. Then, the target process knowledge consists of information about specified process-relevant sensor ranges, such as minimum and maximum sensor values. In the mentioned example, the allowed pressure could be between three and four bar. The last knowledge type is the inspection knowledge, which is generated by the results of the abnormality identification. Hereby, important information are time behaviour, way of appearance of the abnormality or the influence to the system. Hereby, it should be noted that an industrial automation system consist of mechanics, electrics, electronics, and software parts.

With respect to the time behaviour, it was found out, that an abnormality can develop in different ways [9]. It can develop abruptly, such as due to a sudden damage from outside, or intermittently, such as due to a temporary loose contact. Furthermore, an abnormality can develop as a drift, such as in case of a battery capacity loss or as fluctuation, if a controller is busy. Then, the way an abnormality appears can be systematic, such as by wear or random. In order to estimate how severe a fault affects a system, it is significant to know if the fault is locally limited or if it spreads globally over the essential parts of the whole system. Concerning the example of the pressure leak, the leak could increase steadily by mechanic wear. Thus, a pressure loss could express as systematic drift, which could lead to system wide problem. Last but not least, information about the way a fault developed are crucial for the abnormality identification process. In this concept, signal sequences of all process-relevant sensors are recorded, in order to offer valuable clues to the alteration of system behaviour to the point of the fault.

Since, these knowledge types and the information about the system behaviour is used for the abnormality identification and abnormality inspection process, they will be explained in the following in detail.

A. *Abnormality Identification Process in AMIAS*

In AMIAS, the abnormality identification takes place during the operation phase, after a fault has occurred once. The singular occurrence of a specific fault is tolerated, since a more precise inspection knowledge can be generated. The reason is that the fault and in contrary the abnormality occurs under real circumstances during the operation phase. Therefore, the mentioned information about the fault development process and the target process are required. In order to provide any possibility to record fault development process in the system behaviour, a medium called "E-Crash-Box" is used, in which all sensor data are stored during the operation until a fault occurs. Hence, the E-Crash-Box enables the reverse analysis of the system behaviour deviation and so the appearance of the abnormality can be identified precisely. As can be seen in Fig. 1, for the abnormality identification process the recorded sensor data, also called crash-log data is compared with the target process knowledge, in order to figure out in which sensor or set of sensors a deviation is distinguishable.

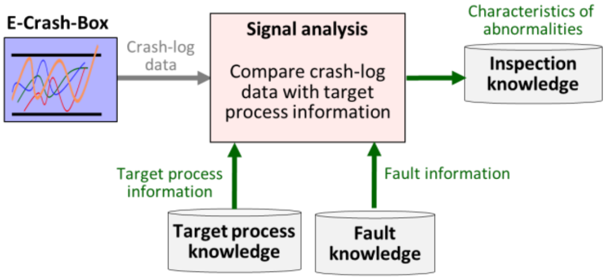

Figure 1. Abnormality identification of AMIAS.

In case of the pressure loss, in the crash-log data a decreasing signal sequence of the pressure sensor could be noticeable, which results in a crossing of the lower target process frontiers of the mentioned three bar, stored in the target process knowledge. To be precise, for such problems, there are many suitable signal analysis methods available. Hereby, the usability of the methods depends on the mentioned abnormality characteristics, such as time behaviour. For drifting and fluctuating abnormalities, especially regression analysis methods or trend checking methods are applicable, because using these methods the behavior of an abnormality between two signal points can be identified very well. For intermitting abnormalities, frequency-based methods are especially applicable, such as Fast Fourier Transformation. With regard to abrupt fault development processes, it must be noted that abnormalities are basically difficult to identify, due to their sudden and immediate transition to a fault. After the abnormalities, which have led to a fault, are identified, the identified characteristics are saved as inspection knowledge. In the pressure loss example, important information could be the drifting behaviour and the measured lowest value of the recorded pressure sensor signals.

B. Abnormality Inspection Process in AMIAS

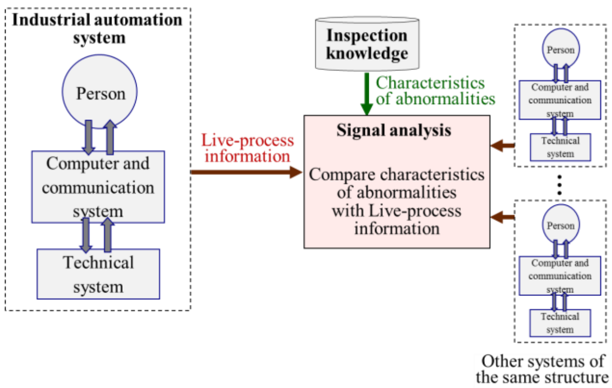

Figure 2. Abnormality identification of AMIAS.

The abnormality inspection is the active and preventive part of the fault prevention, in which it is precautionarily checked during operation phase; if there is any abnormality in the system behaviour. This process is only able to detect certain abnormalities, when exactly these abnormalities are properly identified before. The inspection can be performed according to its requirements permanently, periodically or dynamically in flexible intervals. As shown in Fig. 2, in the abnormality inspection, the results of the abnormality identification, stored in the inspection knowledge, are compared with the live-process information and examined for correlation or deviation.

The depicted live-process information means in this case live-sensor data and further process relevant information, such as properties of the current technical process. Using the example of the pressure loss in the water pipe, it could be examined if the live-signal sequence of the pressure- sensor-data behaves drifting and if there is any value as low as the low value of the stored abnormality. If there is conformity, it can be inferred that the same abnormality has appeared again. In order to automatize the inspection process, the same data and signal analysis methods like in the abnormality identification process can be used, because the abnormalities in the live-process information appear in exact the same manner, as illustrated in the pressure loss example.

A further big advantage in AMIAS is its modular architecture. The singular parts of AMIAS, such as E-Crash-Box, abnormality identification process, abnormality inspection process and the knowledge sets can be distributed, as desired. Amongst others, the inspection knowledge could be on a server, which is accessible in a network or in the internet. So, several systems of the same structure could be checked for abnormalities on basis of the same knowledge. This is a very important ability, due to the mentioned trend of increasing networking and the use of innovative IT-infrastructures, such as Clouds in companies [10].

IV. Evaluation of AMIAS on a Process Automation System

Based on the described concept, a prototypical realization of AMIAS was implemented and linked to a process workstation from the German industrial automation manufacturer Festo. The whole prototype was implemented in Java and consists of five modules. The abnormality identification and abnormality inspection functions were implemented each in one module, in order to encapsulate the functionality for future system adaptions. For the abnormality identification and inspection process of this prototype, it was decided to use different analysis methods, according to the mentioned characteristics of the abnormalities. In order to have a big qualitative support of signal analysis methods, Matlab is applied in AMIAS. For intermitting abnormalities, which shows a periodic unsteady behaviour, or for fluctuating abnormalities, which shows an aperiodic unsteady behavior, a frequency-based analysis method seemed to be applicable. Many of these methods were investigated and finally the Fast Fourier Transformation (FFT) was applied. The decision was made due to benefits, such as less computing time and high performance of the FFT [11]. On the contrary, for drifting abnormalities the Standard Deviation algorithm was implemented [12]. The reason for the Standard Deviation was its simple calculation process and its precision.

Then, in a further module, the E-Crash-Box was implemented. Elementary, it consists of a MySQL database and a logging-thread, which enables the saving of the data stream from the process workstation. For the mentioned fault knowledge, target process knowledge and inspection knowledge a further MySQL database was created.

A. *Simulation of Fault Developments and Evaluation of the Results*

For the process workstation different fault scenarios were developed, such as the explained pressure loss in a water tube or an intermittent loss of power in a pump. In order to simulate the according fault developments, hardware- and software-based regulating screws were integrated, in order to enforce a deviation in the process behaviour up to a breakdown of the technical process.

In case of the simulation of a pressure loss, a mechanic valve was step-wise opened until the required amount of water could be no more afforded and the technical process had to be stopped. At this point, it must be noted that during the whole simulation the system behaviour was recorded in the E-Crash-Box. In the next step, the fault was diagnosed manually and the fault knowledge was generated, as already explained in the concept chapter. Afterwards the software-based abnormality identification was performed according to Fig. 1. As the result, the abnormality identification showed that a drift in the pressure signal sequence occurred and that the admitted sensor-range was exceeded. In this way, 10 different fault development simulations were performed, in order to get expressive results.

In conclusion, 83% of the simulated fault developments abnormalities were identified correctly. It should be noted, that each of the 10 simulation scenarios were repeated 20 times to get more experimental variance.

Furthermore, the abnormality inspection was tested with the same fault development scenarios. For example, in case of the air pressure loss, the valve was opened in different ways until the abnormality inspection triggered an alarm. As already explained, the same analysis methods of the abnormality identification were implemented in the abnormality inspection process, as well. As source information, the two different information types, depicted in Fig. 2 were used. Firstly, the results of the abnormality identification, saved as inspection knowledge in the database were used as input. Moreover, the required live-process information were cached and with it some specific information, such as max-level, min-level and mean value of the pressure sensor were calculated. In the following step, the cached sensor-data, the calculated specific information and the inspection knowledge of the previous pressure loss was compared with each other. Hereby, a deviation between the live-sensor values and the stored abnormality values could be calculated. For a perfect validity, the abnormality inspection process was repeated with each of the other 10 different fault development simulations 20 times. As conclusion, the abnormality inspection could identify approximately 80% of the simulated faults. In this way, the efficiency of the concept and the prototype could be well evaluated and consequently, the availability of the workstation could be increased and the breakdowns could be obviously reduced.

V. Evaluation of AMIAS on a Process Automation System

The paper presented a concept for fault prevention for current and future industrial automation systems using an abnormality management concept. On one hand, with this concept it is possible to identify abnormalities after a fault has occurred, by means of recorded fault development data. On the other hand, industrial automation systems can be checked for the identified abnormalities, in future. In this concept, aspects of future projects, such as “Industry 4.0,” and “Internet of things” were regarded. In the upcoming months, the prototype will be evaluated on different types of systems.

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